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Target Systems and Decision-Making to Increase Production Sustainability

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Abstract

Many industrial companies are trying to improve their operation's sustainability. However, these efforts towards change are usually governed by economic considerations. This serves to neglect or at least diminish the perceivable relevance of ecologic or social consequences for investigated alternatives. This paper discusses the implications of multi-criterial target systems which extend the scope of considerations beyond economics to support the realisation of proactive environmental strategies. A special focus is set on the definition of targets as well as decision-making in brown-field planning projects. The findings are applied in a simulation-based study on the parameterisation of an energy-sensitive production control strategy.

Keywords: Target systems; Brown-field planning projects; Sustainability; Energy-sensitive production strategy; Multi-objective genetic algorithm; NSGA-II

1. Introduction

Legislators across the world are pushing for the use of clean energy, high energy efficiency and ergonomic work environments. Similarly, customers and shareholders expect companies to work towards sustainable operations. Following the UN definition of the term, this includes ecologic, economic and social targets [1]. Yet, actual decision-making processes are usually governed by economic considerations. Still, the environmental strategy of an organisation has tremendous influence on its approach towards sustainable change and can be classified on a scale from defensive to proactive [2,3]. Defensive strategies regard environmental aspects as a constraint imposed by official bodies, while proactive understand them as an autonomous target figure. In between these two, accommodative approaches can be identified, where environmental actions surpass legal demands to create economic advantages.

Decision-making processes which focus too much on the economics are problematic because important ecologic and social factors may be disregarded or need to be assessed on a monetary basis. Especially in factory planning projects, this serves to neglect or diminish the consideration of non-economic consequences by decision makers. At the same time, decision-makers occupying different roles in companies will focus on different target figures.

Emphasising ecologic and social aspects in the decision-making process can serve to support the realisation of proactive environmental strategies and to foster change towards more sustainable production operations. This paper discusses how multi-criterial target systems can be systematically included in brown-field factory planning projects. Arguably, this approach may also be applied in green-field projects. Yet, brown-field was focussed upon for its emphasis on less structural change and greater cost pressure. A potential decision problem in such projects is the selection and optimal parameterisation of an energy-sensitive production control strategy to increase sustainability. This is hereafter exemplified using a case study from the automotive industry, specifically the body shop, which is introduced in Section 2. In the following, some general considerations on decision-making theory as well as the definition of target systems will be introduced before a case-study-specific target system is presented and possible decision-making procedures are outlined. Section 4 discusses how the initial problem was then investigated using material flow simulation and multi-objective genetic algorithms. The corresponding results are also discussed in this section.

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2. Problem definition and case study

Car body shops in countries with high labour costs make use of highly automated equipment which is designed and operated for maximum quality and productivity. Nonetheless, efficiency improvements at minimum cost are expected and sought on a regular basis. A promising approach can be the introduction of energy-sensitive production control strategies. Their implementation is associated with low costs, as primarily organisational changes are needed, but also poses high risks concerning process disruptions. Yet, they can serve to increase the sustainability of a production site if carefully planned.

Deciding on the most suitable strategy to implement and the parameters it should use is, however, a difficile task. This is hereafter exemplified in a case study which investigates a car body shop in a common fish bone structure with 4 manual assembly stations and a finishing area (light tunnel) on the main production line. The assembly stations are supplied by 2 fully automated facilities (subsystems) each, which produce front doors for 3-door variants (FD3), front and rear doors for 5-door variants (FD5/RD5), bonnets, tailgates and wings. All of these subsystems are decoupled from the mainline through buffers. Fig. 1 depicts the corresponding layout structure.

For the operation of the subsystems two energy-sensitive production strategy have been suggested: eniKanban [5] and ConEnIP [6]. eniKanban is, in essence, a Kanban solution which links production control to equipment control. The idea is to operate the equipment in a way that joins multiple short idle periods to fewer but longer ones, during which energy savings can be achieved by shutting down machinery. This is facilitated by stopping production and switching off machines and infrastructure when buffers are full and starting them when a lower threshold is reached. Both the buffer's size and minimal content must be parameterised per subsystem.

ConEnIP, on the other hand, tries to limit the necessary power input of the entire system. For this purpose, a queuing system for production jobs is introduced which will only allow production facilities (e.g. subsystems) to operate when a job and sufficient power capacity are available. Once an entity finishes all jobs it is shut down for a minimal period of time, freeing power capacity. Jobs are created and added to queue when a certain amount of buffered parts have been used (i.e. left the buffer). The parameters of this strategy are the job size and number of jobs per subsystem (the product of which is the buffer size of the decoupling buffer), the priority strategy for the ConEnIP job queue, the minimal shutdown time for subsystems and the maximal power to be consumed by the entire production system. The latter can be segmented over time, i.e. for the day (6:00–20:59) and the night (21:00–5:59).

In order to decide on the strategy and the respective parameters, the above system is simulated to collect data for calculating suitable target figures according to the target system. Parameters of the strategies are integer numbers from within a predetermined range with equidistant step size (e.g. buffer size = n, n ϵ {4, 6, 8, 10}). The use of simulation is preferable as it ensures a low probability for process disruptions during the testing and implementation of a strategy.

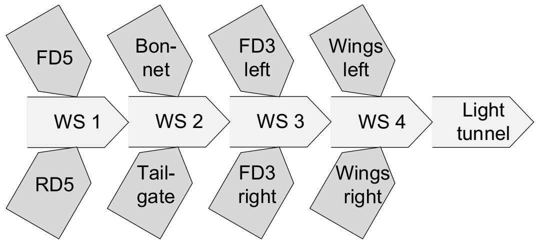

Fig. 1. Structure of the exemplary production facility [4].

3. Decision theory-based approach for decision-making

In order to reach greater sustainability in complex problems some insights into decision theory are valuable. Hence, a brief introduction into the matter is presented hereafter, followed by a case-study-driven discussion of target systems and decision-making procedures.

3.1. Basics from decision theory

The description of the underlying problem reveals its complexity: Several target criteria are relevant, it has to be decided on an energy-sensitive production strategy and its concrete implementation by setting the parameters listed in the previous section and the results are dependent on various uncertain influencing factors such as the intended output, factor prices etc. For structuring such complex decision fields a drawback on fundamental thoughts of decision theory is meaningful [7]. According to decision theory, in a systematic decision-making process the alternatives have to be evaluated with respect to the one or more relevant target criteria and against the background of one or more scenarios bundling the expected outcomes of relevant influencing factors from inside and outside a company. As a central part of this evaluation, the expected effects of the alternatives on the target criteria have to be identified, analysed and forecast by using implicit or explicit result functions that model the relationship between alternatives, influencing factors and target criteria. Concluding, target criteria, alternatives, scenarios (influencing factors) as well as result functions and their results are constitutive elements of decision problems as well as the models representing them. Since the target system is the focal point of all problem solving activities concerning these elements (including the evaluation of alternatives), the forming of a target system is focused in the next step.

3.2. Forming a target system

In the introduction it was argued that contemporary production strategies should be directed towards the criteria of sustainability. Thus, a target system for brown-field planning should comprise the economic as well as ecological and social targets that are influenced by the alternatives under consideration. Since technical targets such as capacity and productivity are also often discussed in the context of decisions on production strategies, the question arises how such targets are coupled with the economic, ecological and social targets focused by the concept of sustainability. Fig. 2 presents the answer: Technology enables contributions to sustainability and especially to sustainable production by a higher resource efficiency, less emissions, better working conditions etc. Thus, technological targets can be seen as a prerequisite of the fulfilment of economic as well as ecological and social targets.

Fig. 2 is an initial point for forming target systems in specific decision problems. It implies the necessity to determine

- which concrete economic, ecological and social targets should be included in the decision-making process and in which way this should be done, as well as
- how to handle technological targets.

Drawing back to decision theory again, it has to be noted that the target system should express the preferences of the decision maker concerning the type of targets, the extent of their realization, the risk concerning their fulfilment and the time in which the results are achieved.

Concerning the type of target criteria as well as the economic, ecological and social dimensions of sustainability, it is suggested to

- take the general target system of a company with its economic, ecological and social goals as a starting point,
- analyse which of these targets are influenced by the alternatives under consideration,
- include the identified target criteria directly in the target system or define other criteria as representatives,
- assure the measurability of the criteria,
- combine them to a system of target criteria that is transparent as well as free of overlapping and allows the target criteria to be fulfilled independently and
- (possibly) take their different relevance into account by ranking or weighting them.

For taking the extent of target fulfilment into account, functions of the utility of the decision maker in dependence of this degree may be formulated. These may include linear and non-linear functions as well as minimal or threshold values. Concerning risk, either certainty is assumed or the risk preference is determined against the background of the possible target criteria values. The inclusion of time preferences is important especially for long-term decision-making. For the economic dimension it is common to discount cash flows of different periods for calculating a net present value under consideration of the time value of money [8].

The second question raised above concerns technological targets. Their importance clearly argues for including them in the target system. However, due to their character as prerequisite of economic, ecological and social targets this will probably result in double counting effects which might distort the results. Thus, it is suggested to build a hierarchical target system including technical target criteria at one level and the target criteria influenced by them at a different level. Additionally, the relationship between technical and other criteria should be comprised. The identification and definition of technological target systems can be handled analogously to the other targets. One difference might be that not the target system of the company but the other target criteria form the initial point.

Starting from the “meta targets” of sustainability and taking the aforementioned aspects into account (including the limitation to targets influenced by the alternatives), a target system for the problem described in Section 2 is derived as follows:

- Economic sustainability is measured by the profit that is yielded by the alternatives under consideration. For a long-term evaluation, a net present value should be preferred. Since the time horizon of analysis is rather short here, the profit (as the dominant monetary short-term target figure of companies) is an adequate measure.
- Ecological sustainability is evaluated using the carbon footprint – as the most prominent ecological target measure with respect to energy consumption at present.
- For social sustainability hardly aggregate measures do exist. However, this is no problem here: The only relevant social effect of energy-sensitive production strategies is the number of night/day working hours of the subsystems. Thus, this number is taken as target figure representing social sustainability.
- Technologically-oriented effects of the production strategies concern the output of car bodies, the use of electricity and the share of electricity generated from renewable energy sources (RES). According to the means-end character of technological targets outlined above as well as the fact that these figures all concern economic and/or ecological and social targets, they are located at the second level of the resulting target hierarchy that is shown in Fig. 3.

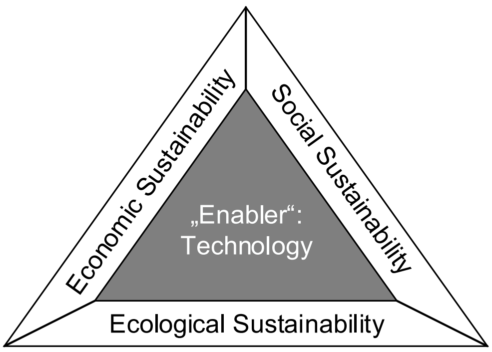

Fig. 2. Technology as an “enabler” for sustainability (cf. [3]).

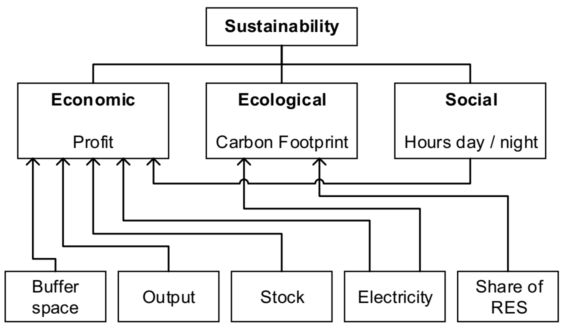

Fig. 3. Target system for the case study.

Fig. 3 omits the underlying connection of the distribution of work over time with the share of RES and hours day/night. This is done as the distribution is not strictly a technical indicator, while still having an effect on the aforementioned.

Concluding, it has to be mentioned that the share of night/day working hours play a double role: On the one hand, it serves as a target figure representing the effects on social sustainability, on the other hand it influences production costs and, thus, profit. The next section discusses how this specific multi-criteria decision-making problem can be solved.

3.3. Decision-making procedures

In general, multi-criteria decision-making (MCDM) problems can be classified according to the number of alternatives – into problems with a limited, discrete number of alternatives (multi-attribute decision-making (MADM)) and problems with an infinite/very large number of alternatives (multi-objective decision-making (MODM)) [9,10]. The decision problem characterized in Section 2 comprises sub-problems of both types: The choice of an energy-sensitive or an alternative production strategy out of few number of available strategies can be interpreted as being of the MADM-type; in contrast, the determination of the decision parameters concretising each strategy shows MODM-characteristics due to the very high (if not infinite) number of possible parameter settings.

In such a situation, different decision-making strategies are on hand:

- The entire problem may be interpreted as a MODM problem so that strategies and parameters are chosen simultaneously.
- The decision problem can be split into sub-problems (of MADM- and MODM-type) and solved stepwise: by first choosing a strategy and then determining the parameters for the chosen strategy or by first optimising the parameters for all optional strategies and then selecting the preferable strategy.

Due to the specific problem characteristics, the simultaneous problem-solving way does not seem to be advisable (due to a high computing effort and the easy divisibility of the problem). The first successive option causes less effort but implies the danger of choosing the wrong strategy because of a missing concretisation of the strategies, the second way shows opposite effects. A compromise could be a preliminary rough determination of parameters, followed by strategy selection and the final fine setting of parameters. In the following section, the procedure of concretising parameters is shown for the example of the ConEnIP strategy (which might be a selected or optional one).

Beforehand, the methods for solving MCDM problems shall be briefly introduced. For MADM problems, a huge variety of methods do exist with most of them (such as Utility Value Analysis, Analytic Hierarchy Process and Multi-Attribute Utility Theory) calculating a final utility value as a result of quantitative measures of the fulfilment of the single targets which are weighted according to the target's relevance. These methods assume compensation of a low fulfilment of single targets – thus, exclusive criteria have to be considered before applying one of these methods [7,8].

MODM methods typically first identify and eliminate inefficient (dominated) solutions. Afterwards, from the resulting efficient solutions the one is selected that best fulfils the targets with respect to the individual preferences of a decision maker. Alternatively, a couple of alternatives can be preselected that fulfil the targets on a high level (from the perspective of one or more decision maker(s)). For this selection step, different procedures may be applied, e.g. a stepwise selection according to a ranking of targets or, again, the use of aggregated utility values [10].

The following section shows how simulation-assisted MODM can be applied to identify suitable parameters, after a control strategy has been preselected using MADM.

4. Application and discussion of results

The investigation of multiple production control strategies in order to determine their optimal parameters is a time consuming task. Full factorial analysis for stochastic problems with n parameters and m steps yield n^m parameter sets [11]. The use of meta-heuristics, e.g. genetic algorithms, helps to minimise the effort at the risk of only finding local optima by applying a limited, directed search on the search space. Still, this can, depending on the complexity, still be tedious work.

Accordingly, the case study described in Section 2 is investigated under the assumption that ConEnIP has to be concretised following the split MADM-MODM-procedure outlined in Section 3.3. The following sections detail how the NSGA-II genetic algorithm (cf. [12]) has been applied for the search for Pareto-optimal parameter sets for the target system defined in Section 3.2 and results thereof are presented.

4.1. Implementation and experiments

The production system introduced in Section 2 has been modelled in the discrete-event simulation software Siemens Tecnomatix Plant Simulation [6]. Stochastic influences are equipment breakdowns, which are randomly introduced in the simulation. Furthermore, the ConEnIP control strategy has been implemented in the model. For each of the parameters introduced in Section 2 between 4 and 10 steps were predetermined considering constraints such as available space, etc.

Each simulation run yields a multitude of data which is used to evaluate individual parameter sets. For the purpose of this investigation, the following indicators are calculated:

- Output of car bodies,
- Production costs (based on profit model discussed in [4]),
- CO_2 equivalent for used electricity, and
- Night working hours of the subsystems.

The earlier two can optionally be used to calculate the profit of the production system as the difference of revenues (as product of output and unit price) and costs. Following [4], the costs include both variable and fixed costs for energy and intermediate storage of parts. In order to investigate the influence of volatile electricity prices, the calculation of variable energy costs is time-dependent. The basis for this are Germany's electricity spot market prices on June 8th 2015. This day was selected as it was determined as reasonable average for a summer day, considering the energy mix. The spot market prices were retrieved from EPEX for the blocks business (9:00-16:59), rush hour (17:00-20:59) and off-peak (21:00-8:59). From these a weighted average for the day has been calculated which was used to determine a relative deviation factor for each time block. According to the respective time in the simulation, these factors are multiplied with the average electricity price for industrial customers (0.1402 €/kWh) and the consumed electricity (kWh) to calculate the resulting costs.

Labour costs for working hours, both during day and night, were not considered in the calculation of costs. While this contrasts with the target system formulated in Section 3.2, the simplification was necessary, as no generally agreeable hourly wage could be identified.

The CO_2 equivalent is determined on the basis of the 2014 equivalent of the German energy mix (609 g/kWh). Since the basis for this number also includes renewably generated electricity, an equivalent for just conventionally sourced electricity was calculated (825.4 g/kWh). After having determined the share of conventionally generated electricity for every 15 minutes, this coefficient and the energy mix of June 8th 2015 are used to calculate the CO_2 equivalent.

Following the reasoning of the introductory paragraphs of this section, genetic algorithms were chosen to determine the most suitable parameters. Plant Simulation includes features which allow for this task. These are, however, based on a weighted sum evaluation of multiple objectives. As decision makers will focus on different target figures in the target system, it is understandable that agreeing on specific weights can be difficult. Furthermore, the contribution of individual target figures to the evaluation and selection procedures of the meta-heuristic will not be transparent and more balanced solutions could be lost in favour of very extreme ones.

In order to be able to decide on the most suitable set of parameters, the use of multi-objective genetic algorithms, which aim to find Pareto-optimal solutions on a per-objective-basis, is more promising. Hence, an NSGA-II-based algorithm has been implemented in Python using the DEAP library [13]. This implementation adapts a DEAP-based reimplementation of the original NSGA-II algorithm [14]. Instead of a simulated binary crossover a uniform crossover has been used to account for the ordered integer coding of individuals (i.e. entire gens are exchanged at random).

The Python script is called from the simulation when an experiment/optimisation commences. It is responsible for generating parameter sets (individuals) as well as configuring and starting the evaluation of these in the simulation. This is done on a per-generation basis, making use of the Experiment Manager tool in Plant Simulation. Once all individuals of a generation are evaluated, the Python script continues to select the fittest individuals from the joined population of parents and children. New children are generated from the resulting population using the crossover and the mutation operators.

During this iterative process, data is exchanged between the simulation and the python script using a PostgreSQL database. This database stores information on all evaluated generations and individuals. The latter is also used to ensure that identical individuals occurring during the course of the experiment are not evaluated multiple times but previous results are reused. In the end, a final population of the fittest individuals is exported for a final MODM process, which determines the most suitable parameter set for the problem.

Here, this setup has been used to process experiments which included 100 generations (plus an additional randomly generated parental generation) with 60 individuals each. In total, no more than 6060 individuals need to be evaluated. To account for stochastic deviations, each individual is investigated 5 times for 90 days of production and the simulation output is averaged between these runs. While the confidence in these averages is low, they mitigate the effect of outliers. The final generation may, in a later step, be evaluated using more runs, either in its entirety or just focusing on selected individuals, to produce results with higher statistical confidence.

4.2. Results

Following the discussion in Section 3.2, technical indicators will influence economic, ecologic and social target figures. However, the final decision-making processes (typically carried out in middle and higher management) are often prepared on lower hierarchy levels of the company (e.g. by simulation engineers), where technical indicators are deemed more important. For the presented case study it could be hypothesized that an optimisation targeting costs and output instead of just profit (either supplementing CO_2 equivalent and night working hours as optimisation targets) could yield different results. Accordingly, two independent optimisations with 3 and 4 target figures have been executed.

Fig. 4 depicts the results of the final generation from the profit-based optimisation for the CO_2 equivalent and the night working hours relating to possible profits. It is apparent, that several disconnected fronts of parameter sets with approximately similar profits but more highly varying CO_2 equivalent exist. The same applies for night working hours.

In general, the following relations can be identified:

- greater profit coincide with higher CO_2 equivalent;

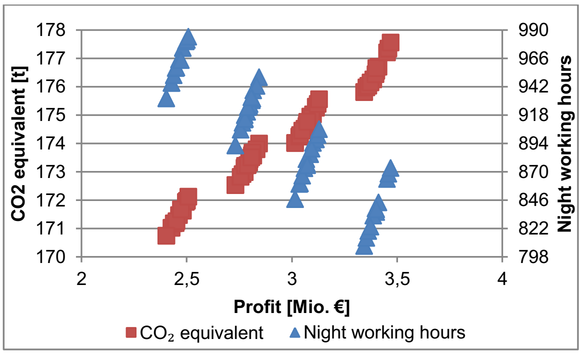

Fig. 4. CO_2 equivalent and night working hours relating to profits for parameter sets of the final generation from profit-based optimisation.

- fewer night working hours coincide with higher CO_2 equivalent (cf. Fig. 4, y-position of fronts left to right);
- within the identified fronts (see Fig. 4) more night working hours coincide with greater profit but more profit can be generated with fewer night working hours.

Concluding from these results it can be stated that there is always a larger group of parameter sets (front) which appear preferable considering one target figure as the dominant one. Hence, the target figures should be ranked so decision makers may eliminate less favourable solutions in a step-by-step process to identify the best choice. For the problem at hand, the front with the highest profits could be chosen and from it the parameter set with the lowest CO_2 equivalent selected. This would also coincide with the lowest night working hours.

Once a selection has been made, it may be necessary to normalise the parameters to account for random effects of the optimisation. For instance, when the selected parameter sets suggest different sizes for buffers decoupling similar subsystems, these should be aligned. Furthermore, a validation using more runs is advisable to ensure lack of confidence in the results from the optimisation is negligible.

Analysing the results from the second optimisation, which used 4 target figures (output, costs, CO_2 equivalent and night working hours), similar dependencies and trends (compared to the above) can be identified. This discourages the hypothesis that different results could be yielded. Fig. 5 shows that the hypothesis appears, indeed, unfounded. The results of both optimisations match each other quite closely. Hence, the use of fewer target figures is preferable as it would ease the final selection of the most suitable parameter set.

In conclusion, the experimental setup was capable of identifying Pareto-optimal parameter sets for the previously selected energy-sensitive production control strategy ConEnIP. These can then be used in a subsequent decision-making process. It is still advisable to collect all technical indicators even if they are not used in the immediate optimisation. Thus, they may be referenced in the decision-making process, especially in lower levels of hierarchy, for instance, to eliminate results which violate a predefined threshold for the least output desirable. Additionally, the results can be used for evaluating the preferability of different (energy-sensitive) production strategies with respect to sustainability targets.

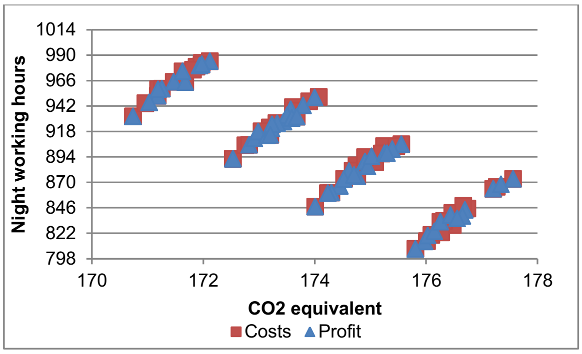

Fig. 5. Night working hours and CO_2 equivalent for parameter sets of final generations of both optimisations (3 and 4 target figures).

5. Conclusion and Outlook

The paper presents an approach for designing and controlling production strategies that are aiming at contributing to sustainability. The approach combines insights and methods from decision theory and multi-criteria decision-making with those of production planning and control. Through simulation, a high flexibility and applicability at different company-levels are achieved. The approach has been exemplified for an energy-sensitive production control strategy in a car body shop.

Further research should address different topics: The target-forming process outlined in Section 3 and the resulting target system as well as the decision-making procedures should be discussed and elaborated more deeply in order to develop mature generic processes, procedures and sustainability-oriented target systems for groups of production planning problems. Additionally, the different roles and targets of the decision makers at company levels and departments should be analysed in order to design and establish coordination mechanisms that ensure consistent target systems and corresponding actions at different company levels and departments. The approach suggested here can form a part of such coordination mechanisms since it is able to reveal the trade-offs between the achievements of different technical, ecological, economic and social targets.

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